

Robust multiobjective scheme for closed-loop supply chains by considering financial criteria and scenarios

John Willmer Escobar^{a*}, William Adolfo Hormaza Peña^b and Rafael Guillermo García-Cáceres^c

^aDepartment of Accounting and Finance, Universidad del Valle, Cali, Colombia

^bSelf Employed, Cali, Colombia

^cSchool of Industrial Engineering, Universidad Pedagógica y Tecnológica UPTC, Tunja, Colombia

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ABSTRACT

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This paper considers the closed-loop supply chain design problem by examining financial criteria and uncertainty in the parameters. A robust multiobjective optimization methodology is proposed by considering financial measures such as maximizing the net present value (NPV) and minimizing the financial risk (FR). The proposed methodology integrates various multiobjective optimization elements based on epsilon constraints and robustness measurements through the FePIA (named after the four steps of the procedure: Feature–Perturbation–Impact–Analysis) methodology. Similarly, an analysis of the parameter variability using scenarios was considered. The proposed method's efficiency was tested with real information from a multinational company operating in Colombia. The results show the effectiveness of the methodology in addressing real problems associated with supply chain design.

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1. Introduction

A supply chain involves all the direct and indirect aspects leading to the solution required for customers in a macro view of an organization. The supply chain includes components that range from suppliers of raw materials, carriers, warehouses, small suppliers, manufacturers or producers, distribution centers, intermediaries, and end customers (Delgoshai et al., 2019) (Fig. 1).

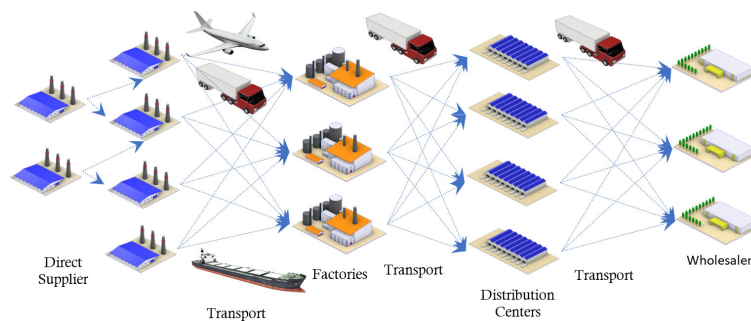


Fig. 1. Supply Chain

* Corresponding author

E-mail: john.wilmer.escobar@correounivalle.edu.co (J. W. Escobar)

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In addition, the study of supply chains focuses not only on the objects or materials that are mobilized but also on the economic aspects, costs involved in each of the stages, services, interruptions, environmental impact, and profits of the system (Escobar, 2017; Tordecilla-Madera et al., 2018). Supply chain management includes three decision levels within an organization: strategic, tactical, and operational (Escobar, 2009; Escobar, 2017), impacting decision-making at the corporate level. The strategic level refers to long-term decisions, such as the configuration of the supply chain, selection, and allocation of suppliers and customers, the number, size, and location of facilities, the types of products to be manufactured, acquisition of credits and financing, and the return obtained after investing in infrastructure. The tactical level refers to medium-term decisions, which include inventory management, production, and transportation selection. Finally, the operational level is more specific, and the planning and execution decisions are made for the actions chosen at other levels. At this level, decisions typically correspond to NP-hard problems (Escobar, 2017; Buritica et al., 2017).

Return on investment and inherent risk are critical factors at the strategic level due to the variability or uncertainty in demand. The net present value (NPV) supports public or private companies in making investment decisions (Juhász, 2011). Similarly, financial risk (FR) in supply chains could be defined as the probability of an economic decision that does not result in the expected profit level (Escobar et al., 2019). Therefore, financial risk determines the probability of a viable business (Bagajewicz & Barbaro, 2003).

In addition, supply chains must face uncertainty factors in each stage; for this reason, companies must adapt to unforeseen events, and this fact must be structured into the system to make it reliable (Polo et al., 2019). According to Ali et al. (2004), robustness is defined as preserving a system's characteristics even though it is subjected to an environment with fluctuating behavior. Klibi & Martel (2012) argued that a supply chain must maintain the same response if subjected to different scenarios. Therefore, the supply design must be sustainable regardless of disturbances by measuring and applying robustness, responsiveness, and resilience characteristics.

Companies' competitiveness forces them to design and create strategies that optimize resources and maximize profits with minimal expenses. Additionally, due to the constant disturbances in a supply chain, it is necessary to formulate techniques that guarantee that businesses give investors confidence. In this way, the locations of the warehouses, production plants (PP), distribution centers (DC), or collection and repair centers (RC) allow for the prediction of strategic decisions to optimize the supply chain.

This paper proposes a methodology for supply chain design considering strategic and tactical decisions, such as opening production lines, distribution centers, supplier selection, transport selection arrangements, and inventory expansion, in a closed-cycle supply chain. The proposed mathematical model seeks to maximize investment benefits and minimize financial risk by considering various scenarios. The proposed methodology integrates supply chain elements, such as multiobjective optimization based on epsilon constraints and robustness, in a model with uncertain demand through the FePIA methodology. The main contribution of this study is considering and integrating quantitative aspects such as multiobjective optimization, scenario-based optimization, closed supply chain with recovery of products, financial measures, and robustness to find a methodology that fits into the strategic and tactical levels of the company's supply chain operations. From the literature reviewed, no previous studies have considered integrating all these aspects, allowing for a more precise supply decision-making process. In addition, the application of this method to a real case study measures the solution strategy's efficiency, allowing its scalability to other companies with similar characteristics. Indeed, the highlighted aspects of the proposed approach are the financial risk formulation within a robust stochastic multiobjective environment, the scenario consideration in the proposed model's mathematical structure, and the robustness measure by the FePIA methodology within a multiobjective mathematical model.

The paper proceeds as follows. Section 2 presents a literature review of the problems associated with a supply chain optimization with multiple objectives that considers financial criteria and scenarios and identifies the relevance of the research work and the foundations for the recognized problem. Section 3 shows the detailed formulation of the problem with a mixed-integer linear mathematical model and the details of the proposed solution methodology. In Section 4, the experiments are conducted, and the results are obtained. Finally, in Section 5, the investigation's conclusions are presented, and possible future works are established.

2. Literature Review

In supply chain studies, various types of decisions can be classified and differentiated. The types of decisions are strategic (long-term), tactical (medium-term), and operational (short-term). Long-term decisions consider the location of distribution centers, plants, and the best distribution of the flows and establish a network between the distribution centers and the suppliers and customers. Tactical decisions are related to the flow of products, inventory levels, and forecast of demand. Operational or short-term decisions involve a truck and routing scheduling and temporary storage in cross-docking and distribution centers.

Given that the proposed methodology has a strategic and tactical focus, similar problems within supply chain designs separately involve closed green supply chains, financial criteria, stochastic issues, multiobjective optimization, and robustness, which serve as the basis for the considered problem.

2.1. Closed Green Supply Chains

Recently, the importance of reverse logistics has grown due to reprocessing costs, mismanagement, the environmental impact of production processes, and the increasing advantages of recovering products for sustainable production. Reverse logistics can be defined as a set of processes to reuse products returned by customers through repair or refurbishment (Srivastava, 2007). Studies have been published on reverse logistics issues (Amin & Zhang, 2013; García-Cáceres & Escobar, 2016; Paz & Escobar, 2019). A mixed-integer linear programming model is presented in that research to minimize total costs, considering demand and random returns.

Allaoui et al. (2018) presented a critical literature review of operations research methods to design sustainable supply chains. In that work, a new two-stage hybrid solution methodology was proposed for the considered problem. In the first stage, partner selection is performed using hybrid multicriteria decision-making based on the analytical hierarchy process (AHP) method and the ordered weighted average aggregation (OWA) method. The results in the first stage were used in the second stage to develop a multiobjective mathematical model for supply chain design.

Heidari-Fathian and Pasandideh (2018) considered sustainability criteria in a blood supply chain by presenting a multiobjective mixed-integer mathematical programming model. This work examined the total cost minimization of the supply chain and minimized the overall environmental impacts of the network's activities. Finally, Baghalian et al. (2013) presented a robust mixed-integer nonlinear mathematical model to determine profit performance in an agri-food supply chain.

2.2. Economic and Financial criteria in Supply Chain

Some authors have considered economic criteria for supply chain design. Kovačić and Bogataj (2017) proposed a supply chain model to minimize the NPV in energy production by considering reverse logistics decisions for supplying electricity to the main grid. Polo et al. (2019) applied the methodology proposed by Ali et al. (2004) in a mixed-integer nonlinear programming model to maximize the economic value added (EVA), considering the influence of disturbances on the system performance, showing the impact on the costs. Carvajal et al. (2019) proposed optimizing a sugarcane supply chain model to maximize the NPV, considering the influence of the climate, the machinery's capacity, and the availability of refinery plant biofuel.

On the other hand, the FR can be defined as the probability that an economic decision results in an established performance level in a given time or the probability that the NPV is equal to or less than zero (Escobar et al., 2019). Escobar et al. (2019) presented a multiobjective mixed-integer linear programming model based on the idea proposed by Bagajewicz and Barbaro (2003) to maximize the NPV and minimize the FR of a supply chain. Likewise, Escobar (2017) presented a distribution network model for maximizing the NPV by considering the generation of scenarios to denote demand variability.

2.3. Stochastic Supply Chains

Guillén et al. (2005) considered the design and modernization of a supply chain consisting of several production plants, warehouses, markets, and associated distribution systems. The effects of uncertainty in the production scenario were considered by using a two-stage stochastic model. The problem's objective was evaluated, taking into account the benefit over the time horizon and the resulting demand's satisfaction.

Azaron et al. (2008) proposed a multiobjective stochastic programming model to minimize costs and the probability of not reaching a specific budget. The decisions involved the supply chain structure, the opening or closing of plants and distribution centers. In contrast, Klibi and Martel (2012) applied simulations to determine the scenarios that could generate risks in a supply chain and assessed their incidents.

Chen and Lee (2004) proposed a multiproduct, multistage, multiperiod programming model to address immeasurable goals for a multilevel supply network with uncertain market demands and product prices. The demand uncertainty was modeled as a series of discrete scenarios with known probabilities and fuzzy sets to describe the incompatibility of sellers and buyers with product prices.

2.4. Robust Supply Chains

Robustness can be found in different environments, such as biology, economics, electricity, robotics, and mechanics. It is defined as a system's ability to keep its internal functions and properties constant, regardless of external disturbances (Monostori, 2018).

Ben-Tal and Nemirovski (1999) developed a linear programming model with a feasible robust solution that generated a matrix in which the parameters and uncertain variables were located according to the corresponding probability scenarios and determined the optimal solution through computational traceability. Pishvae et al. (2011) proposed a robust optimization model to address uncertainty in supply chain design problems by evaluating the robustness of solutions, minimizing costs, and determining strategic decisions for plant and distribution center openings. Jabbarzadeh et al. (2017) applied robustness to a multiobjective supply chain model in an electrical network by maximizing efficiency and minimizing losses with contradictory environmental and economic effects. In particular, robust systems provide a positive boost to reduce environmental impacts. Other practical application cases have been proposed by Banasik et al. (2017) and Habibi et al. (2017).

Kim et al. (2018) considered a reverse logistics model for supply chains that applied a robustness methodology to maximize profit in a textile plant. In that work, the performance model was improved through the application of two robust counterparts. Delgoshaei et al. (2019) used a robustness measurement method to carry out a supply chain's programming, considering machinery failures and preventive maintenance, resulting in lower production losses and a reduction in unexpected failure times and achieving stability in sales fulfillment. Metaheuristic methods such as the ant colony and simulated annealing were used to solve the problem.

Alavi and Jabbarzadeh (2018) presented a robust stochastic optimization model for the supply network design problem while accounting for commercial credit and bank financial resources. This robust model helped to determine the number and location of facilities as well as financing decisions. The goal was to maximize expected supply chain profits under demand uncertainty. Ruimin et al. (2016) considered a robust network that included multiple plants, collection centers, demand zones, and products and consisted of direct and reverse supply chains. First, a robust multiobjective mixed-integer nonlinear programming model was proposed to solve the problem under consideration. The methodology called FePIA was introduced by Ali et al. (2004). This research investigated the robustness of resource allocations to tasks in parallel and distributed systems. The methodology's main aspects were a mathematical description of a robustness metric for resource allocation concerning desired system performance features against multiple perturbations in multiple systems and environmental conditions and a procedure for deriving a robustness metric for an arbitrary system. A few authors have extended the FePIA methodology to evaluate robustness in supply chains (Polo et al., 2019; Polo et al., 2020).

In the reviewed literature, no work was found that integrates robust multiobjective mathematical models with financial criteria and scenarios for a closed supply chain to maximize the system's robustness with a scheme extended from electric system problems. It is essential to mention that the literature considering the union of multiobjective models applying robustness methods is scarce, especially considering financial risk.

3. Proposed Methodology

In this paper, a general robust optimization model for closed-loop supply chains is proposed in which the relationship between the steps comprising the chain is analyzed. This analysis includes decisions to open and locate PPs, DCs, and RCs and decisions related to the forward and reverse flow of products. The mathematical model considers two objectives: maximizing the NPV by considering investments in infrastructure and minimizing the FR by considering strategies to maintain the infrastructure over time despite increased disruptions. Finally, the model uses reverse logistics problems in different equiprobable scenarios. The design of the chain under study is shown in Fig. 2.

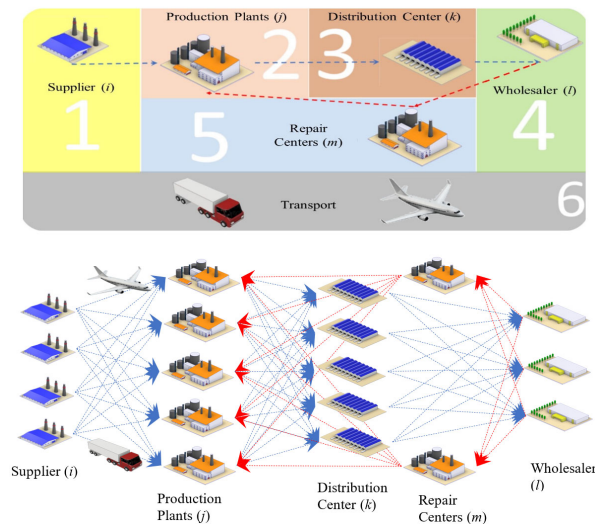


Fig. 2. Considered Supply Chain

The proposed model utilizes the following assumptions:

- The plants have different business areas, each with different lines and products.
- Production lines that handle only distribution at the national level are selected, and exports are not considered.
- The production lines are located in different parts of the country.
- Imported raw materials are assumed to be from national ports.
- New distribution centers are assumed to be in different areas to satisfy demand.
- Reverse logistics processes are contemplated to recover materials with defects from wholesale clients, in which some reprocessing must be carried out.

The development of the mathematical model and the definition of sets, variables and parameters are presented as follows:

3.1. Sets

i	= Suppliers; $i = 1, 2, \dots, I$
j	= Productive Plants; $j = 1, 2, \dots, J$
k	= Distribution Centers; $k = 1, 2, \dots, K$
p	= Products; $p = 1, 2, \dots, P$
q	= Raw Materials; $q = 1, 2, \dots, Q$
l	= Wholesale Customers; $l = 1, 2, \dots, L$
m	= Collection and Repair Centers; $m = 1, 2, \dots, M$
t	= Time Periods; $t = 1, 2, \dots, T$
s	= Scenarios; $s = 1, 2, \dots, S$

3.2. Parameters

φ_s	= Probability of occurrence of scenarios
Ω_s	= Expected value of the NPV in scenario s [\$]
DEM_{plt}^s	= Demand of product p at customer l in period t according to scenario s [unit / t]
UPT_p	= Units per ton of product p [unit / t]
$UMTPT_q$	= Units per ton of raw material q [unit / t]
PRE_{pl}	= Price of product p for customer l [\$/t]
CCD_{pk}	= Handling cost of product p at DC k [\$/unit]
$CTCD_{pkl}$	= Transportation cost of product p from DC k to customer l [\$/t]
$CIPP_{qj}$	= Inventory cost of raw material q at plant j [\$/t]
CPP_{pj}	= Manufacturing cost of product p in plant j [\$/unit]
$CTPP_{pjk}$	= Transportation cost of product p from plant j to DC k [\$/t]
CMT_q	= Cost of raw material q [\$/unit]
$CTMT_{qij}$	= Transportation cost of raw material q from supplier i to plant j [\$/t]
CCR_{mp}	= Cost of RC m per product p [\$/t]
$CTCR_{ml}$	= Transportation cost from customer l to repairing center m [\$/t]
$CTCP_{mj}$	= Transportation cost from RC m to plant j [\$/t]
$CATCD_k$	= Transportation capacity CD k per period [ton]
$CACD_k$	= Storage capacity of CD k [ton]
$CAPNPP_{jp}$	= Production capacity of plant j to process product p [ton / t]
DT_k	= Availability of transport cargo from DC k [%]
OEE_j	= Total effectiveness of plant equipment j [%]
$CAPP_j$	= Storage capacity of repairing plant j [ton]
CAR_m	= Reprocessing capacity of RC m [ton / t]

$CACR_m$	= Storage capacity of RC m [ton / t]
$COFPP_j$	= Fixed costs in plant j per period [\$/t]
$COFCD_k$	= Fixed costs in DC k per period [\$/t]
$COFCR_m$	= Fixed costs in RC m per period [\$/t]
$CMT P_{qp}$	= Raw material components q in product p [%]
IPP_j	= Initial investment to install plant j [\$]
ICD_k	= Initial investment to install DC k [\$]
ICR_m	= Initial investment to install RC m [\$]
$TIMP$	= Income tax rate
APP_{jt}	= Amortization and depreciation of plant j in period t [\$]
ACD_{kt}	= Amortization and depreciation of DC k in period t [\$]
ACR_{mt}	= Amortization and depreciation of RC m in period t [\$]
DEF	= Percentage of maximum defects allowed by the company
$WACC$	= Weighted average cost of capital

3.3. Variables

M_{ijt}^{qps}	= Amount of raw material q of product p sent from supplier i to plant j in period t in scenario s [ton]
I_{qjt}^s	= Final inventory of raw material q at plant j in period t in scenario s [ton]
X_{jkt}^{ps}	= Amount of product p sent from plant j to DC k in period t in scenario s [ton]
T_{pkt}^s	= Final inventory of product p at DC k in period t in scenario s [ton]
Y_{klt}^{ps}	= Amount of product p sent from DC k to customer l in period t in scenario s [ton]
U_{mt}^{ps}	= Amount of product p under repair RC m in period t in scenario s [ton]
Z_{lmt}^{ps}	= Amount of product p returned from customer l to RC m in period t in scenario s [ton]
W_{mjt}^{ps}	= Amount of product p returned from RC m to plant j in period t in scenario s [ton]
V_{mt}^{ps}	= Final inventory of products p at the RC m in the period t in the scenario s [ton]
OPP_j	= 1 if plant j must be opened, 0 otherwise
OCD_k	= 1 if DC k must be opened, 0 otherwise
OCR_m	= 1 if RC m must be opened, 0 otherwise

3.4. Objective Functions

3.4.1. Maximization of the Net Present Value (NPV)

The first objective function is to maximize the weighted net present value (NPV) over the possible scenarios for the defined periods. This function is calculated with the sum of the probability of the free cash flow possible scenarios brought to the present minus the initial investment value if it is desired to keep the facilities in operation, as shown in Eq. (1).

$$\max NPV = \sum_{s=1}^S \varphi_s \left[\sum_{t=1}^T \frac{FCF_{st}}{(1+WACC)^t} \right] - I_0 \quad (1)$$

The breakdown of the components of (1) is as follows:

$$FCF_{st} = [EN_{st} - Cost_{st}]^+ * (1 - TIMP) + Demp_t \quad \forall s, t \quad (2)$$

$$I_0 = \sum_{j=1}^J IPP_j OPP_j + \sum_{k=1}^K ICD_k OCD_k + \sum_{m=1}^M ICR_m OCR_m \quad (3)$$

Similarly, the components of Eq. (2) can be detailed as follows. Revenue (4) is equal to the sum of the products' prices multiplied by the number of products that reach the end customers.

$$EN_{st} = \sum_{k=1}^K \sum_{p=1}^P \sum_{l=1}^L PRE_{pl} Y_{klt}^{ps} \quad \forall s, t \quad (4)$$

The expression $Cost_{st}$ corresponds to the sum of the expenses involved in the supply chain, such as transportation costs (5), handling costs (6), production costs (7), distribution costs (8), costs associated with raw materials and repair values (9) and $FixedCost_t$ (10).

$$\sum_{l=1}^L \sum_{p=1}^P \sum_{k=1}^K CTCD_{pkl} Y_{klt}^{ps} + \sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K CTPP_{pj k} X_{jkt}^{ps} + \sum_{m=1}^M \sum_{p=1}^P \sum_{l=1}^L CTCR_{ml} Z_{lmt}^{ps} + \sum_{m=1}^M \sum_{p=1}^P \sum_{j=1}^J CTC P_{mj} W_{mjt}^{ps} + \sum_{q=1}^Q \sum_{p=1}^P \sum_{i=1}^I \sum_{j=1}^J CTMT_{qij} M_{ijt}^{qps} \quad \forall s, t \tag{5}$$

$$\sum_{p=1}^P \sum_{k=1}^K UPT_p CCD_{pk} T_{pkt}^s + \sum_{j=1}^J \sum_{q=1}^Q CIPP_{qj} I_{qjt}^s \quad \forall s, t \tag{6}$$

$$\sum_{p=1}^P \sum_{j=1}^J \sum_{k=1}^K UPT_p CPP_{pj} X_{jkt}^{ps} \quad \forall s, t \tag{7}$$

$$\sum_{m=1}^M \sum_{p=1}^P \sum_{l=1}^L CCR_{mp} Z_{lmt}^{ps} Demp_t \quad \forall s, t \tag{8}$$

$$\sum_{q=1}^Q \sum_{p=1}^P \sum_{i=1}^I \sum_{j=1}^J UMTPT_q CMT_q M_{ijt}^{qps} \quad \forall s, t \tag{9}$$

$$FixedCost_t = \sum_{j=1}^J COFPP_j OPP_j + \sum_{k=1}^K COFCD_k OCD_k + \sum_{m=1}^M COFCR_m OCR_m \quad \forall s, t \tag{10}$$

$$Demp_t = \sum_{j=1}^J APP_j OPP_j + \sum_{k=1}^K ACD_k OCD_k + \sum_{m=1}^M ACR_m OCR_m \quad \forall s, t \tag{11}$$

3.4.2. Minimization of the Financial Risk (FR)

The second objective function seeks to minimize the FR assumed by companies when investing (Bagajewicz & Barbaro, 2003). According to Eppen et al. (1989), FR is associated with the impossibility of achieving the required benefit. It assumes that the real risk is less than the expected benefit:

$$Min FR = \sum_s \varphi_s \delta_s(x, \Omega) \Rightarrow Min FR = \sum_s \varphi_s (\Omega_s - NPV_s) \tag{12}$$

That is, the variables $Z_s(x, \Omega)$ and $\delta_s(x, \Omega)$ depend on the result of the first objective function (1):

$$\sum_{s=1}^S \varphi_s \left[\sum_{t=1}^T \frac{FCF_{st}}{(1 + CCPP)^t} \right] - I_0 < \sum_{s=1}^S \Omega_s \tag{13}$$

A more natural way to understand the trade-off between risk and NPV_s is through the cumulative risk curve, which indicates that the NPV_s gain is proportional to risk. The $NPV_s = \sum_{t=1}^T \frac{FCF_{st}}{(1 + WACC)^t} - I_0$ is defined as the Net Present Value of the scenario s . A more significant benefit is obtained with a higher risk (Escobar et al., 2020). Similarly, there would be no risk if the NPV_s is more significant than Ω .

3.5. Constraints

Demand constraints: In the proposed model, we have assumed that the demand should be met. However, we have required that the dispatch variable to clients be less than or equal to the demand requested.

$$\sum_{k=1}^K Y_{klt}^{ps} \leq DEM_{plt}^s \quad \forall l \in L, t \in T, s \in S, p \in P \quad (14)$$

Capacity constraints: It is guaranteed that the plants, DCs and RCs do not exceed their operating capacities, considering that the production plants are affected by the total effectiveness of the equipment.

$$\sum_{k=1}^K X_{jkt}^{ps} \leq OPP_j OEE_j CAPNPP_{jp} \quad \forall j \in J, p \in P, t \in T, s \in S \quad (15)$$

$$\sum_{l=1}^L \sum_{p=1}^P Y_{klt}^{ps} \leq OCD_k DT_k CATCD_k \quad \forall k \in K, t \in T, s \in S \quad (16)$$

$$\sum_{p=1}^P U_{mt}^{ps} + \sum_{p=1}^P \sum_{j=1}^J W_{mjt}^{ps} \leq OCR_m CAR_m \quad \forall m \in M, t \in T, s \in S \quad (17)$$

Material balance constraints: This constraint ensures that the nodes that participate in the supply chain have a correct flow of products and materials. In other words, the initial inventory plus the incoming materials is equal to the distributed materials plus the final inventory (Fig. 3).

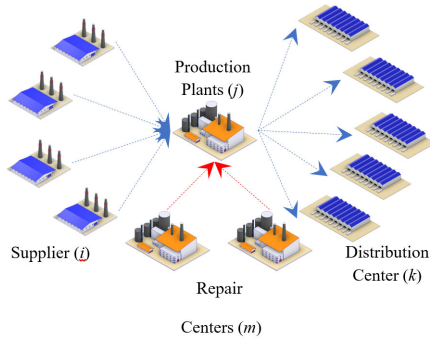


Fig. 3. Balance in Productive Plants

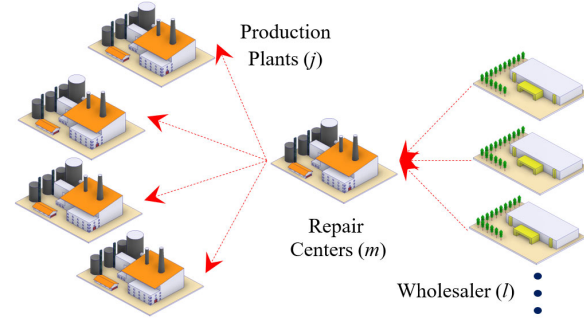


Fig. 4. Balance in Repairing Centers

The equations for the balance of raw materials in the plants are indicated in Eq. (18) and Eq. (19):

$$\sum_{i=1}^J \sum_{p=1}^P M_{ijt}^{qps} = \sum_{p=1}^P \sum_{k=1}^K X_{jkt}^{ps} CMTP_{qp} + I_{ajt}^s \quad \forall t = 1, s \in S, j \in J, q \in Q \quad (18)$$

$$\sum_{i=1}^J \sum_{p=1}^P M_{ijt}^{qps} + I_{ajt-1}^s = \sum_{p=1}^P \sum_{k=1}^K X_{jkt}^{ps} CMTP_{qp} + I_{ajt}^s \quad \forall t \geq 2, s \in S, j \in J, q \in Q \quad (19)$$

Fig. 4 shows the product flows and the balance in the repair centers.

$$\sum_{l=1}^L Z_{lmt}^{ps} + U_{mt}^{ps} = \sum_{j=1}^J W_{mjt}^{ps} + V_{mt}^{ps} \quad \forall m \in M, t = 1, s \in S, p \in P \quad (20)$$

$$\sum_{l=1}^L Z_{lmt}^{ps} + V_{mt-1}^{ps} + U_{mt}^{ps} = \sum_{j=1}^J W_{mjt}^{ps} + V_{mt}^{ps} \quad \forall m \in M, t \geq 2, s \in S, p \in P \quad (21)$$

Constraints of storage capacities: It is guaranteed that the inventories in the nodes do not exceed the storage capacities. Eq. (22) shows the storage capacity in plants, while the storage capacity in DCs is shown in Eq. (23), and the storage capacity in RCs is shown in Eq. (24).

$$\sum_{q=1}^Q I_{qjt}^s \leq OPP_j * CAPP_j \quad \forall j \in J, t \in T, s \in S \tag{22}$$

$$\sum_{p=1}^P T_{pkt}^s \leq OCD_k * CACD_k \quad \forall k \in K, t \in T, s \in S \tag{23}$$

$$\sum_{p=1}^P V_{mt}^{ps} \leq OCR_m * CACR_m \quad \forall m \in M, t \in T, s \in S \tag{24}$$

Raw material consumption constraints. Equation (25) determines the balance of raw material sent for manufacturing the finished product.

$$\sum_{i=1}^I M_{ijt}^{qps} = \sum_{k=1}^K CMT P_{qp} X_{jkt}^{ps} \quad \forall t \in T, s \in S, p \in P, q \in Q, j \in J \tag{25}$$

Constraints of defects. Equation (26) determines the quantity of the defective product in the total demand.

$$\sum_{l=1}^L Z_{lmt}^{ps} = \sum_{l=1}^L DEF * DEM_{plt}^s \quad \forall m \in M, t \in T, s \in S, p \in P \tag{26}$$

Integrality constraints: These equations guarantee that all variables are greater than or equal to zero.

$$X_{jkt}^{ps}, T_{pkt}^s, Y_{klt}^{ps}, U_{mt}^{ps}, Z_{lmt}^{ps}, W_{mjt}^{ps}, M_{ijt}^{qps}, I_{qjt}^s, V_{mt}^{ps} \geq 0 \quad \forall j \in J, k \in K, l \in L, m \in M, q \in Q, p \in P, s \in S, t \in T \tag{27}$$

Financial risk constraints: Additionally, in the second objective function (12), it must be taken into account that this applies only when the NPV does not reach the budgeted value; that is, the difference between the estimated value and the NPV obtained is greater than zero.

$$\delta_s(x, \Omega) \geq \Omega - NPV_s \quad \forall s \tag{28}$$

$$\delta_s(x, \Omega) \geq 0 \quad \forall s \tag{29}$$

3.6. Robustness Measurement

Once the mathematical model's baseline is defined, the robustness methodology is considered and carried out according to the FePIA procedure (Figure 5). Initially, the robustness requirements of the model are determined based on the results of objective functions (1) and (12), and the demand compliance (14) as a performance characteristic is defined as the occupation percentage of plants, DCs, and RCs. Additionally, the possibility of closing plants or distribution centers is contemplated. In the second instance, the disturbance parameters are defined that affect the main elements of the model's performance, as seen in Figure 5. The proposed steps of the FePIA methodology proposed by Ali et al. (2004), Polo et al. (2019), and Polo et al. (2020) can be summarized as follows:

- *Feature:* In this step, the robustness requirements, operating characteristics and performance characteristics are described. They are quantitatively defined as the set Φ describing the performance characteristics of the system, where for each $\phi_r \in \Phi$, a variation of ϕ_r is presented.
- *Perturbation:* This phase describes the perturbation parameters. In fact, $\pi_s \in \Pi$ are the elements of the set of perturbation parameters.
- *Impact:* The effects that the disturbance parameters have on the performance characteristics are identified. Indeed, $\phi_r = f_{rs}(\pi_s)$
- *Analysis:* The variation scale of the characteristics generated by the robustness parameter variation is established. Indeed, for each $\phi_r \in \Phi$, the limit values of π_s that meet the relationships $f_{rs}(\pi_s) = \beta_r^{min}$ and $f_{rs}(\pi_s) = \beta_r^{max}$ must be determined.

The following sections show the steps of the proposed methodology summarized in Fig. 5.

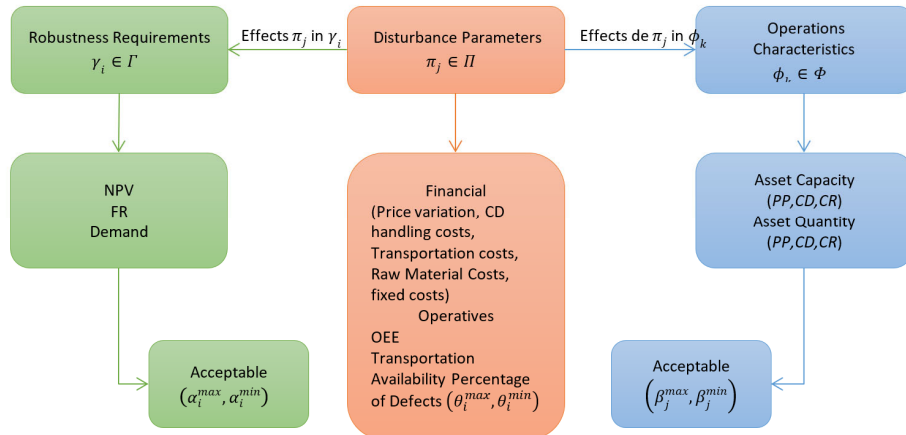


Fig. 5. Robustness Methodology

3.6.1. Definition of Robustness Requirements

As shown in Fig. 5, the robustness requirements Γ that are affected by the disturbance parameter variations must be defined. These requirements $\gamma_i \in \Gamma$ must be measurable and comparable. Initially, the values of the objective functions (%) (1) and (12) are presented to compare the effect of the benefits in standard situations with baseline values (see Table 1). Indeed, the aim of these objectives is to maximize the NPV (1) and minimize the FR (12), which must be consistent with the actions that are performed in the supply chain and the results that are obtained. On the other hand, there is a demand compliance, which is directly related to the performance of the supply chain. Table 1 shows the values established for each of the robustness requirements (% NPV, % FR and % demand).

Table 1

Range of requirements

Γ	Requirements	α_i^{min}	α_i^{max}
γ_1	% NPV	50%	NA
γ_2	% FR	NA	25%
γ_3	% Demand	85%	100%

The definitions of γ_1 to γ_3 are calculated by Eq. (30) to Eq. (32). The maximum (α_i^{max}) and minimum (α_i^{min}) values allowable for these requirements are defined in Table 1.

$$\gamma_1 = \frac{NPV^\pi}{E(NPV)} \quad (30) \quad NPV^\pi: \text{Results of NPV in event } \pi$$

$$\gamma_2 = \frac{FR^\pi}{I_0} \quad (31) \quad FR^\pi: \text{Results in event } \pi$$

$$\gamma_3 = \frac{\sum_{k=1}^K Y_{klt}^{ps\pi}}{DEM_{plt}^s} \quad (32) \quad I_0: \text{Initial investment}$$

$$\sum_{k=1}^K Y_{klt}^{ps\pi}: \text{Sum of the quantity of products } p \text{ sent from DC } k \text{ to customers } l \text{ in scenario } s \text{ in event } \pi$$

$$DEM_{plt}^s: \text{Demand}$$

3.6.2. Definition of Operating Characteristics

The operating characteristics are directly related to the ability of the company to meet the proposed goals. Therefore, they are related to the company's ability to produce, distribute, and operate throughout the supply chain to prevent the requirements from deviating from the established parameters. Table 2 shows the operating characteristics that are taken into account in the design of the supply chain.

Table 2

Range of Characteristics

Φ	Operational Characteristics	β_i^{min}	β_i^{max}
ϕ_1	Percentage of Occupation of Plants	35%	70%
ϕ_2	Percentage of Occupation of Distribution Centers	45%	90%
ϕ_3	Percentage Occupation of Repairing Centers	40%	80%
ϕ_4	Number of Opened Plants	3	5
ϕ_5	Number of Opened Distribution Centers	3	5
ϕ_6	Number of Opened Repairing Centers	2	3

The calculations are performed according to each of the assets' total capacity, as shown in the following equations, and the number of assets required.

$$\phi_1 = \frac{\sum_{k=1}^K \sum_{j=1}^J \sum_{p=1}^P X_{jkt}^{ps\pi}}{\sum_{j=1}^J \sum_{p=1}^P CPP_{jp}} \quad (33) \quad \sum_{k=1}^K \sum_{j=1}^J \sum_{p=1}^P X_{jkt}^{ps\pi} : \text{Sum of the quantity of products } p \text{ produced in PP } j \text{ sent to DC } k \text{ in scenario } s \text{ in event } \pi$$

$$\phi_2 = \frac{\sum_{l=1}^L \sum_{k=1}^K \sum_{p=1}^P Y_{klt}^{ps\pi}}{\sum_{k=1}^K CATCD_k} \quad (34) \quad \sum_{l=1}^L \sum_{k=1}^K \sum_{p=1}^P Y_{klt}^{ps\pi} : \text{Sum of the quantity of products } p \text{ sent from DC } k \text{ sent to customers } l \text{ in scenario } s \text{ in event } \pi$$

$$\phi_3 = \frac{\sum_{p=1}^P \sum_{m=1}^M U_{mt}^{ps} + \sum_{p=1}^P \sum_{j=1}^J \sum_{m=1}^M W_{mjt}^{ps\pi}}{\sum_{m=1}^M CAR_m} \quad (35) \quad \sum_{p=1}^P \sum_{m=1}^M U_{mt}^{ps} + \sum_{p=1}^P \sum_{j=1}^J \sum_{m=1}^M W_{mjt}^{ps\pi} : \text{Sum of the quantity of products reprocessed at RC } m \text{ in scenario } s \text{ in event } \pi$$

$$\phi_4 = \sum_{j=1}^J OPP_{j\pi} \quad (36) \quad \sum_{j=1}^J OPP_{j\pi} : \text{Sum of binary variables of opening PP } j \text{ in event } \pi$$

$$\phi_5 = \sum_{k=1}^K OCD_{k\pi} \quad (37) \quad \sum_{k=1}^K OCD_{k\pi} : \text{Sum of binary variables of opening DC } k \text{ in event } \pi$$

$$\phi_6 = \sum_{m=1}^M OCR_{m\pi} \quad (38) \quad \sum_{m=1}^M OCR_{m\pi} : \text{Sum of binary variables of opening RC } m \text{ in event } \pi$$

3.6.3. Determination of disturbance parameters

The different events $\pi \in \Pi$, in which the requirements Γ and the characteristics Φ of the supply chain are disturbed, are presented in Table 3. This table shows the variations in the parameters $\pi \in \Pi$, generating a set of 33 combinations (3 values for each event) of parameter variations in which the effect of disruptions on the requirements and main characteristics of the supply chain can be evidenced.

Table 3
Applied Perturbations

Π	Parameters	θ			Causes
		θ_i^{min}	θ_i^{med}	θ_i^{max}	
π_1	Price of Product	105	96	94	Market variation, price competition
π_2	Handling costs on CDs	105	110	120	Reprocesses
π_3	General transportation costs	105	115	135	Road problems, blockages and collapses
π_4	Raw Material Costs	102	105	110	Little supply of materials
π_5	Fixed Costs	90	105	115	Administrative and operational cost overruns
π_6	OEE	150	95	80	Machine and production speed problems
π_7	Transportation Available	98	95	90	Road problems, blockages and collapses
π_8	$\pi_1 + \pi_4$				
π_9	$\pi_2 + \pi_3 + \pi_5$				
π_{10}	$\pi_6 + \pi_7$				
π_{11}	$\pi_9 + \pi_{10}$				

4. Computational Results

4.1. Case of Study

The efficiency of the proposed methodology was tested in a mass-consumption company producing personal care items in Colombia. This method is subject to meeting the growing demand and competition that challenges each link in the supply chain. Although the company typically works with strict process control methodologies, waste control, such as World Class Manufacturing (WCM), has deficiencies in all links in the supply chain. In the relations of suppliers and wholesale customers, relationships are generated according to strategic alliances, and disturbances occur at the financial level. Suppliers control the acquisition costs in the company; customers and competition drive product prices, which are very relevant factors in terms of the company's profitability. On the other hand, the relationship with suppliers is essential in stabilizing the flow of raw

materials, which can be affected either by product shortages or by delivery times, directly affecting production and, consequently, demand fulfillment.

For customers, market behavior is crucial for the fulfillment of the company's goals. A market study is required for making strategic decisions, such as increasing production capacity in production plants or opening new plants, opening distribution centers, procuring additional raw materials, reducing fixed costs, and closing production plants or distribution centers. In intermediate nodes such as plants, distribution centers, and repair centers, the flow of products moves from the company's internal assets and strategies such as the Warehouse Management System (WMS). The total effectiveness of the equipment (OEE) is controlled. The value of the OEEs is affected by four factors: fundamentals, quality, performance, and availability. These factors affect profitability and demand compliance. Quality is directly related to the number of compliant products manufactured related to the total number of products made; this is affected by low equipment operation, poor execution of production processes, and irregular defects within the raw materials. The performance is also affected by the machines' speed and operating rate.

The performance can be affected by problems of speed reduction in machines. Constant stops can occur on the lines when there are queues or bottlenecks within the range or a lack of knowledge in operating the machine. Finally, the performance is directly affected by the operating time of the devices and the total work time. The most representative causes of speed reductions are machine failures, emergency damage, or scheduled repairs. However, plant shutdowns can also occur due to a lack of materials that creates machine stoppages when there is insufficient production programming (Muchiri & Pintelon, 2008).

The aim is for the OEE expected values to be above 80%; however, the average value has been at 65% in recent years, which is the starting base of the plant's capacities. On the other hand, there are issues related to inventories, either due to a lack of materials in the plant or online or inefficient scheduling according to the BOM (material lists). These issues are internal problems of the production plant due to high stock levels in the warehouses that store final products. These problems could be generated by inefficient scheduling in dispatches, transport delays, or production, creating production time losses in the plant of up to 5%, directly affecting the OEE of the company, which, to reduce the impact, has chosen to raise process costs up to 80%.

Finally, there are external factors for the company, which are generally related to transport. Along the supply chain between each link, there is an implicit cost of transporting the products or materials moving between them. In this case, this cost is approximately 16% to 18% of production costs, which are affected by different factors: a) natural phenomena such as landslides, earthquakes, storms, or pandemics; b) socioeconomic events such as physical security problems, protest problems, and blockades; and c) effects from public infrastructures, such as airport closures, transport terminals, and deterioration of roads, which are also typical problems in Colombian logistics.

4.2. Computational Results

The proposed methodology was solved using an Intel Core i5 3.1 GHz computer with 8 GB of RAM. The model was programmed in AMPL, and the CPLEX 12.4 solver was used. Mathematical equations (1) to (29) were solved with expected initial data of profit and NPV in terms of the expenses and income obtained for 24 months, considering three equiprobable scenarios (optimistic, pessimistic, base). The results can be seen in Table 4. The values obtained for the initial NPV and FR were defined as the baseline to observe the changes generated with the application of the disturbances. For the solution of the multiobjective model, the epsilon restrictions method (ϵ -Constraint) was used, which consists of restricting one objective function to be optimized with the optimal values of the other objective function (Laumanns et al., 2006; Pérez-Cañedo et al., 2020; Guerriero et al., 2014). In this case, the NPV was restricted with the optimal FR value, as shown in Table 4.

Table 4
Optimal solution for each objective independently

Γ	I
NPV	\$ 2.017.031.145
FR	\$ 3.149.118.855
% Financial Risk	34.5%
Fulfillment of Demand	96.8%

In Fig. 6, the behavior of the initial scenario's two functions and the values expected by the company are shown. In this case, as is sometimes observed, the initial condition was improved. The ideal configuration of assets that better fits the established requirements is presented in the following sections.

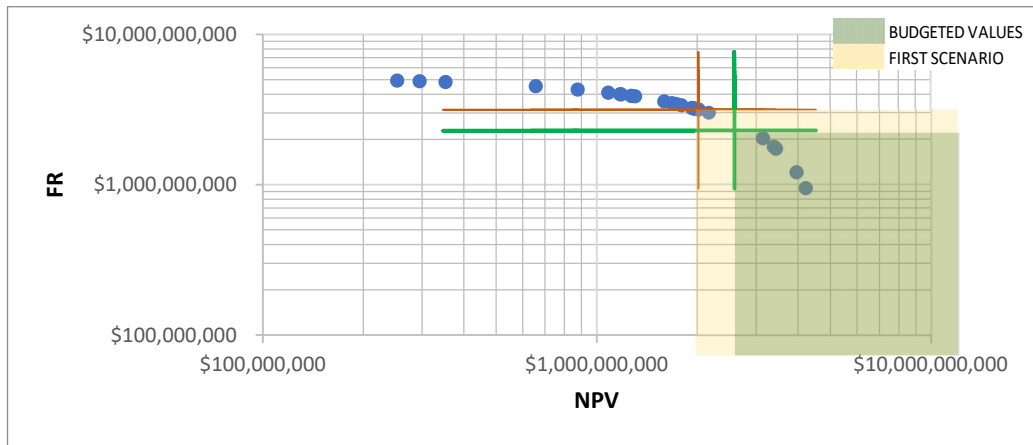


Fig. 6. Pareto solutions front without perturbations

4.2.1. Impact of disturbances on the Supply Chain

The effect of the disruptions on the characteristics and requirements responding to the mathematical formulations $\phi_k = f_{ks}(\pi_s)$ and $\gamma_i = f_{is}(\pi_s)$ was obtained using the parameter data modified according to the scenarios described in the previous section to achieve the results in event II. Table 5 presents the results obtained after running the model with each of the parameters II according to Table 3. The requirements Γ and characteristics Φ vary according to the standards established in Table 1 and Table 2.

Table 5
Impact of disturbances on supply chain design

II	Γ			Φ											
	NPV	FR	Fulfillment of Demand	Occupation of PP			Occupation of DC			Occupation of RC					
				N	+	-	N	+	-	N	+	-			
0.1	\$ 2.017.031.145	\$ 3.149.118.855	96.8%	30.9%	67.8%	43%	4	5	3	4	4	3	3	3	3
1.1	\$ 4.222.251.189	\$ 943.898.812	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
1.2	\$ 252.855.110	\$ 4.913.294.890	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
1.3	-\$ 629.232.908	\$ 5.795.382.908	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
2.1	\$ 2.017.031.145	\$ 3.149.118.855	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
2.2	\$ 2.017.031.145	\$ 3.149.118.855	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
2.3	\$ 2.017.031.145	\$ 3.149.118.855	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
3.1	\$ 2.005.409.213	\$ 3.160.740.787	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
3.2	\$ 1.982.165.350	\$ 3.183.984.651	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
3.3	\$ 1.935.686.569	\$ 3.230.463.431	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
4.1	\$ 1.684.240.510	\$ 3.481.909.491	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
4.2	\$ 1.185.054.557	\$ 3.981.095.443	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
4.3	\$ 353.111.937	\$ 4.813.038.063	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
5.1	\$ 3.440.811.949	\$ 1.725.338.051	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
5.2	\$ 1.305.140.743	\$ 3.861.009.257	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
5.3	-\$ 118.640.062	\$ 5.284.790.062	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
6.1	\$ 2.168.723.089	\$ 2.997.426.911	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
6.2	\$ 1.932.798.639	\$ 3.233.351.361	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
6.3	\$ 1.795.433.336	\$ 3.370.716.664	92.1%	29.7%	64.6%	41%	4	5	3	4	4	3	3	3	3
7.1	\$ 1.594.255.740	\$ 3.571.894.261	93.8%	33.0%	65.7%	42%	4	5	3	4	4	3	3	3	3
7.2	\$ 1.177.309.309	\$ 3.988.840.692	99.1%	33.0%	69.4%	44%	4	5	3	4	4	3	3	3	3
7.3	\$ 877.721.817	\$ 4.288.428.183	96.4%	32.2%	67.5%	43%	4	5	3	4	5	4	3	3	3
8.1	\$ 3.390.274.600	\$ 1.775.875.400	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
8.2	-\$ 579.121.478	\$ 5.745.271.478	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
8.3	-\$ 2.293.152.116	\$ 7.459.302.116	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
9.1	\$ 3.429.190.017	\$ 1.736.959.983	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
9.2	\$ 1.270.274.947	\$ 3.895.875.053	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
9.3	-\$ 199.984.638	\$ 5.366.134.638	96.8%	32.3%	67.8%	43%	4	5	3	4	4	3	3	3	3
10.1	\$ 1.732.140.362	\$ 3.434.009.638	93.8%	31.3%	65.7%	42%	4	5	3	4	4	3	3	3	3
10.2	\$ 1.084.503.942	\$ 4.081.646.058	99.0%	33.0%	69.4%	44%	4	5	3	4	4	3	3	3	3
10.3	\$ 657.223.718	\$ 4.508.926.282	96.4%	32.0%	67.5%	43%	4	5	3	4	4	3	3	3	3
11.1	\$ 3.145.052.465	\$ 2.021.097.535	95.0%	31.7%	66.5%	42%	4	5	3	4	4	3	3	3	3
11.2	\$ 295.109.915	\$ 4.871.040.086	99.1%	33.2%	69.4%	44%	4	5	3	4	4	3	3	3	3
11.3	-\$ 1.687.965.418	\$ 6.854.115.418	96.4%	32.0%	67.5%	43%	4	5	3	4	4	3	3	3	3

As shown in Fig. 7, the NPV presents a positive value for most events, and in some cases, it is above the expected level, as is the FR (Fig. 8). However, negative NPV values are also present. Figure 9 shows that the benefits are above the expected minimum in terms of demand in all events. It can also be observed that regarding the occupation of the plants (Fig. 10), there is an underutilization of assets that may incur additional costs for the company, generating the option of closing production plants for the pessimistic scenario and the use of 5 plants in the optimistic scenario.

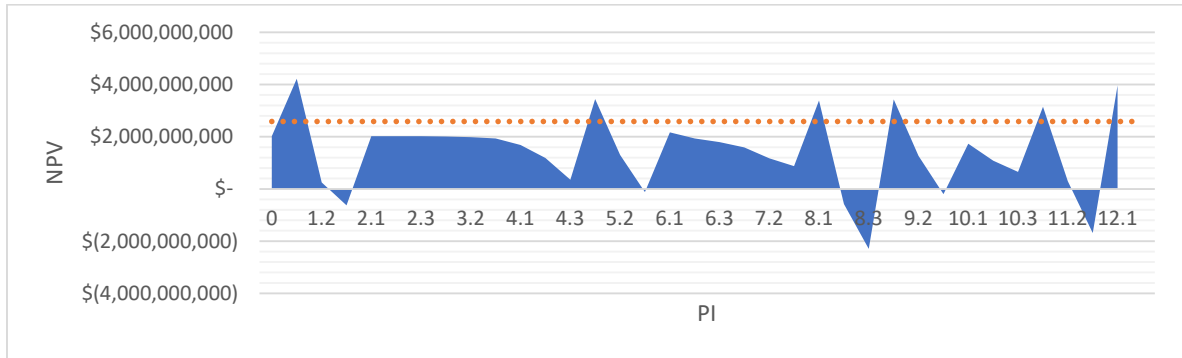


Fig. 7. Performance of NPV (Owner)

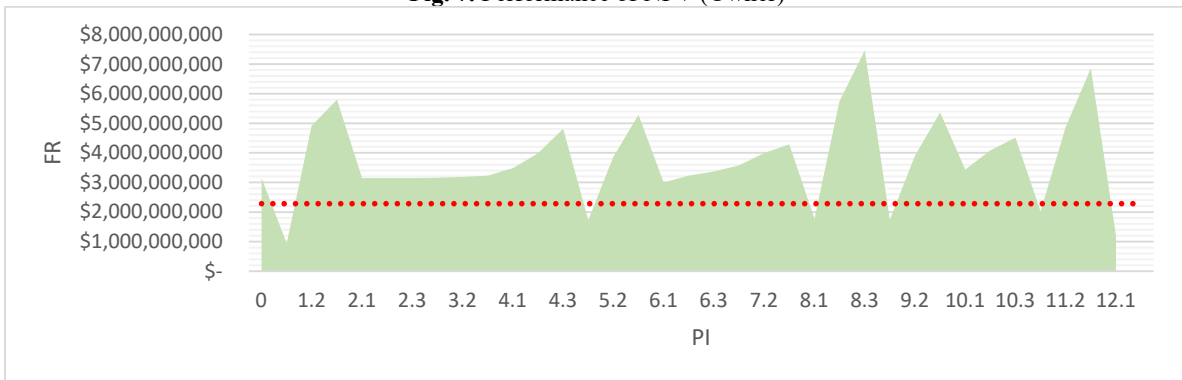


Fig. 8. Performance of FR (Owner)

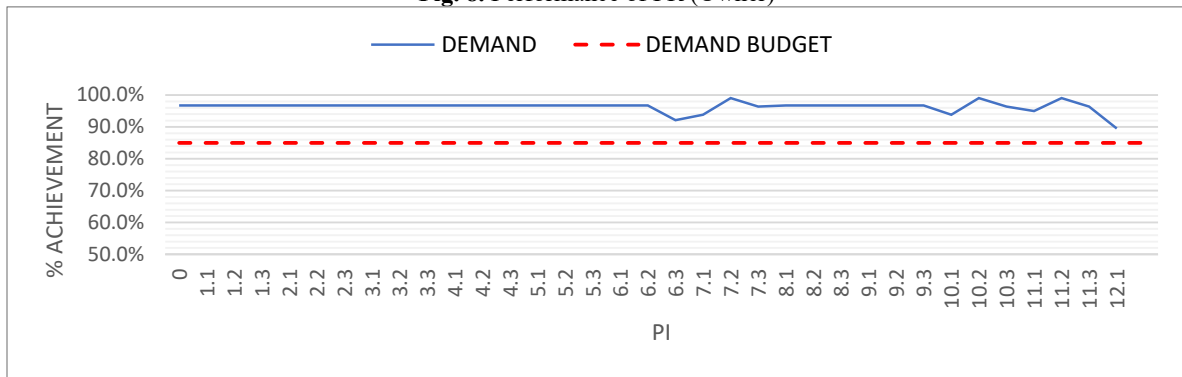


Fig. 9. Fulfillment of Demand (Owner)

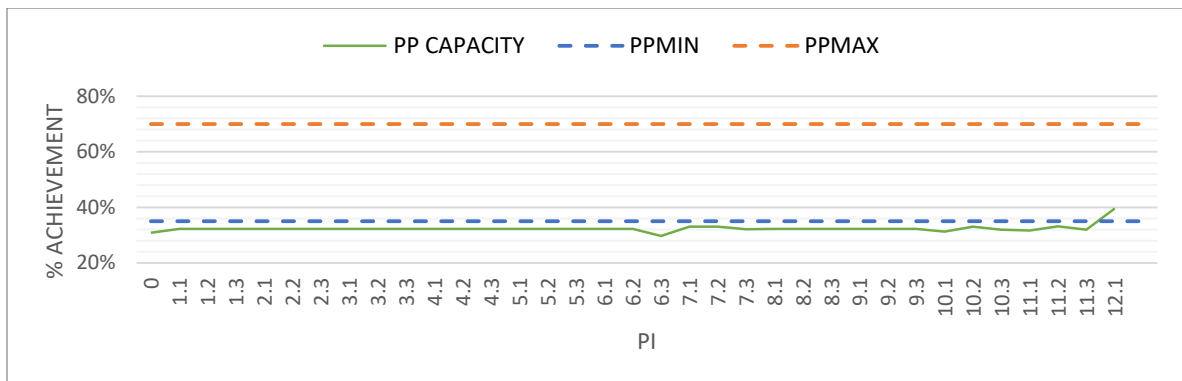


Fig. 10. Occupation of PP (Owner)

Table 6 shows the supply chain configuration results that better support the disturbances within the analyzed models. The better performance results of the NPV and FR are presented, showing the best strategic decision regarding the company's assets, leaving the plants and distribution centers that performed the best in the solution. The two options are the events with the best results regarding the NPV and FR; within the company's requirements is an opening range of PPs and CDs. Therefore, this solution proposes to leave a maximum of 3 PPs and 3 CDs, which generates the decreasing costs reflected in the increase in NPV, slightly sacrificing demand and remaining within the range allowed by the company.

Table 6
Best result of the proposed events

II	NPV	FR	Fulfillment of Demand	Occupation of PP	Occupation of DC	Occupation of RC	PP	DC	RC
12.1	\$ 3.964.730.092	\$ 1.201.419.909	89.5%	39.6%	78.4%	57%	1,2,3	1,2,3	1,2
12.2	\$ 4.414.723.272	\$ 751.426.729	89.5%	40.1%	78.4%	57%	2,3,5	1,2,3	1,2

As shown in Fig. 11 to Fig. 13, there are some disturbance events Π in which the supply chain's response does not meet the company's requirements. These events display the most abrupt parameter changes, such as $\pi_{8,3}$ and $\pi_{11,3}$, which are the most detrimental events to the profitability of the supply chain. However, with robust models, the company's profits are improved, even under some scenarios that showed losses with the initial models. On the other hand, in most cases, the minimum demand compliance requirement is met. Less transport availability and a lower OEE in the PP generate a decrease in this requirement's fulfillment. However, the characteristics themselves are different. The model changes the number of assets within the supply chain; a better PP, CD, and RC occupation can be evidenced, demonstrating that the supply chain must dispense some assets. In Fig. 14 and Fig. 15, the PP and the RC occupations are within the range required by the company. However, the company is unlikely to decrease assets for reasons of demand compliance. Likewise, the CD occupation value is improved to be within the allowed range.

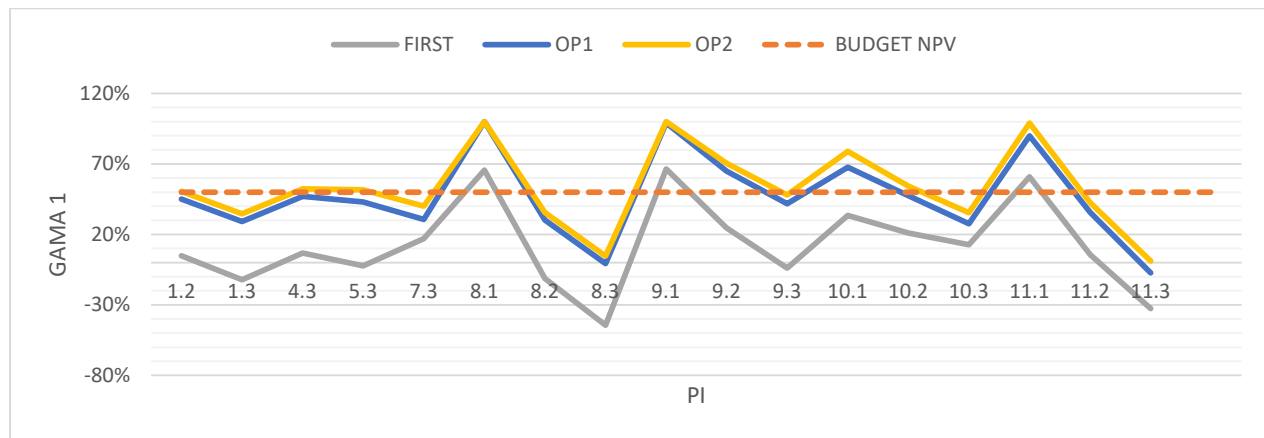


Fig. 11. Net Present Value (Robust Model) (Owner)

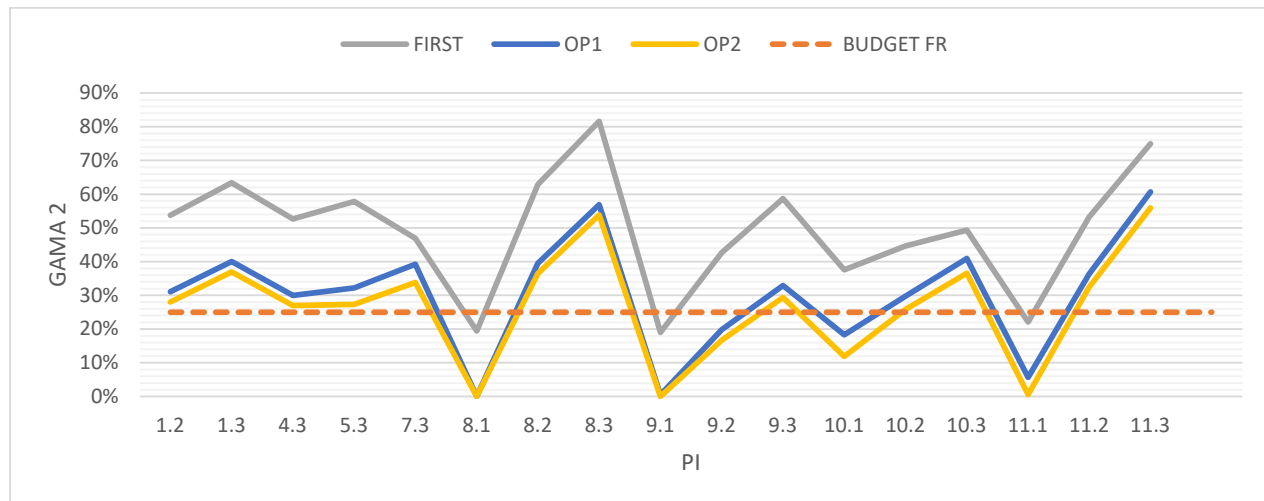


Fig. 12. Financial Risk (Robust Model) (Owner)

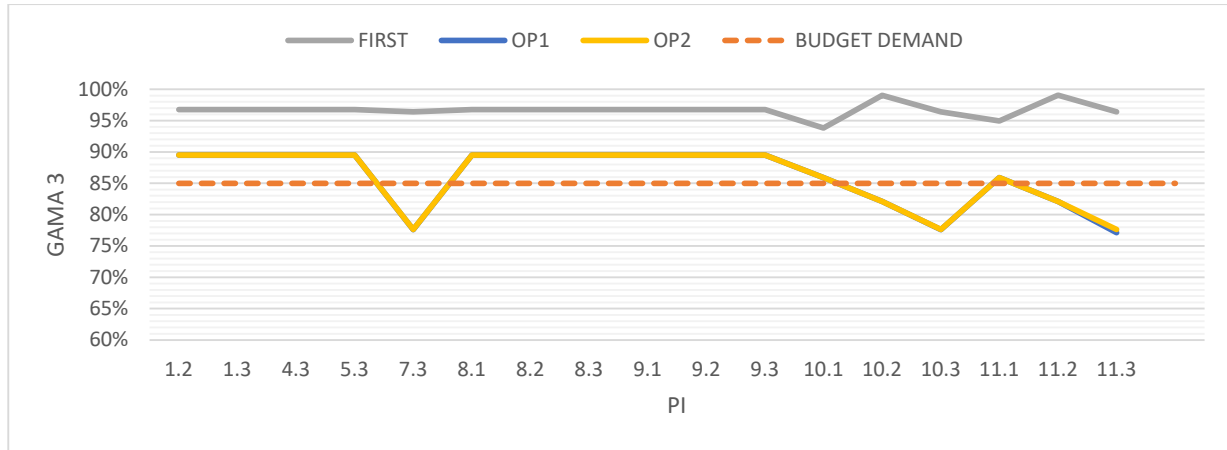


Fig. 13. Fulfillment of Demand (Robust Model) (Owner)

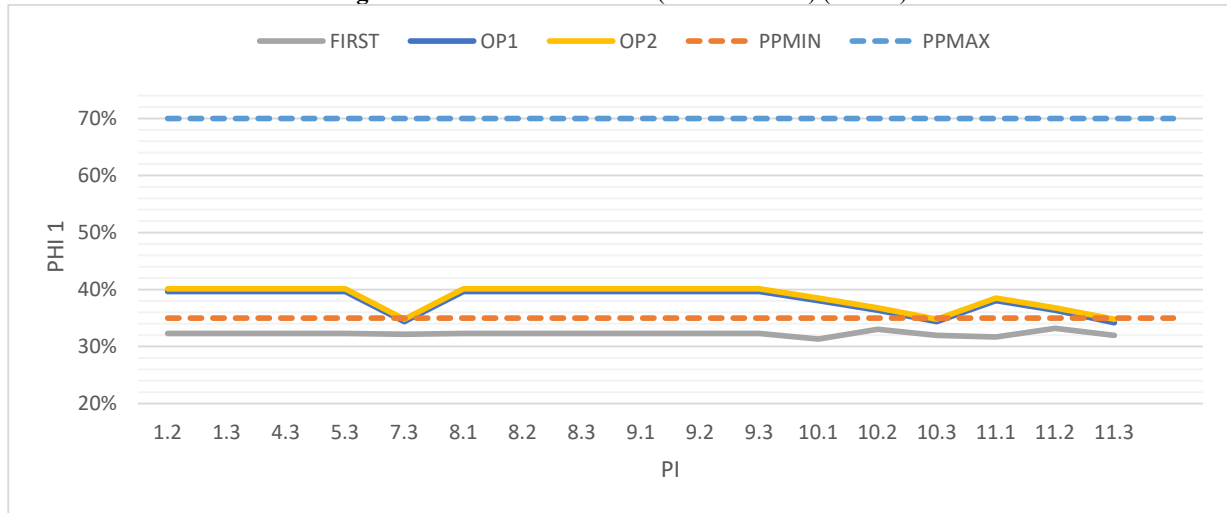


Fig. 14. Occupation of PP (Owner)

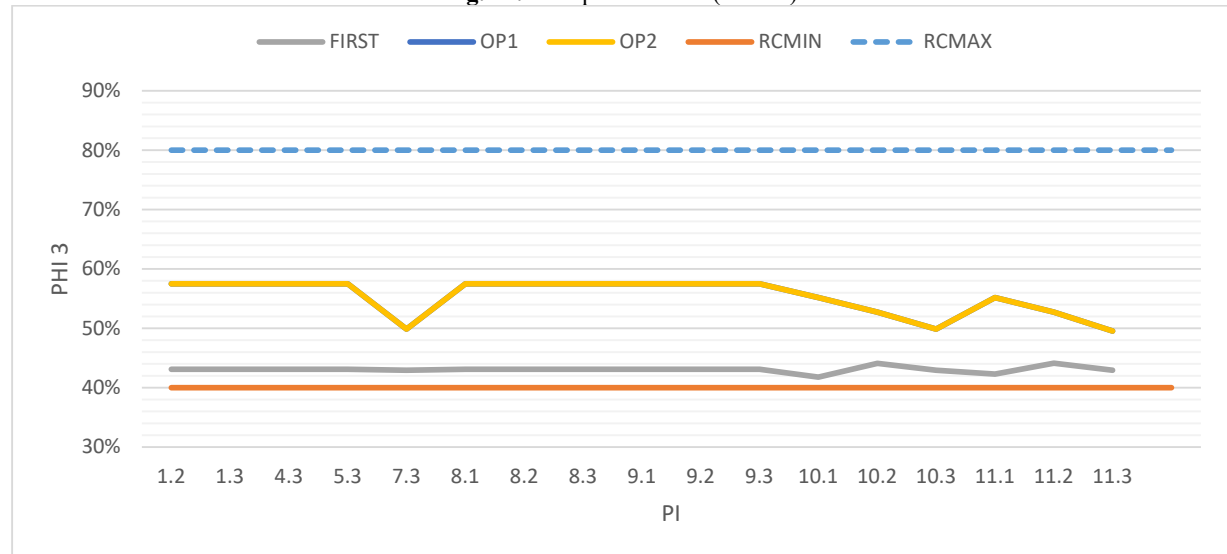


Fig. 15. Occupation of RC (Owner)

The amount of assets the company needs is reduced regarding the generation of fixed costs, transportation costs, and initial investments. In the two presented options, the opened plants are 1, 2, and 3 for Option 1, located in Cali, Pereira, and Tocancipá, and Option 2, Plants 2, 3, and 5 located in Pereira, Tocancipá, and Medellín are opened, with the same DCs and RCs for the two options (DCs 1, 2 and 3 located in Bogotá, Cali and Medellín and RCs 1 and 2 located in Cali and Tocancipá), as shown in Fig. 16.

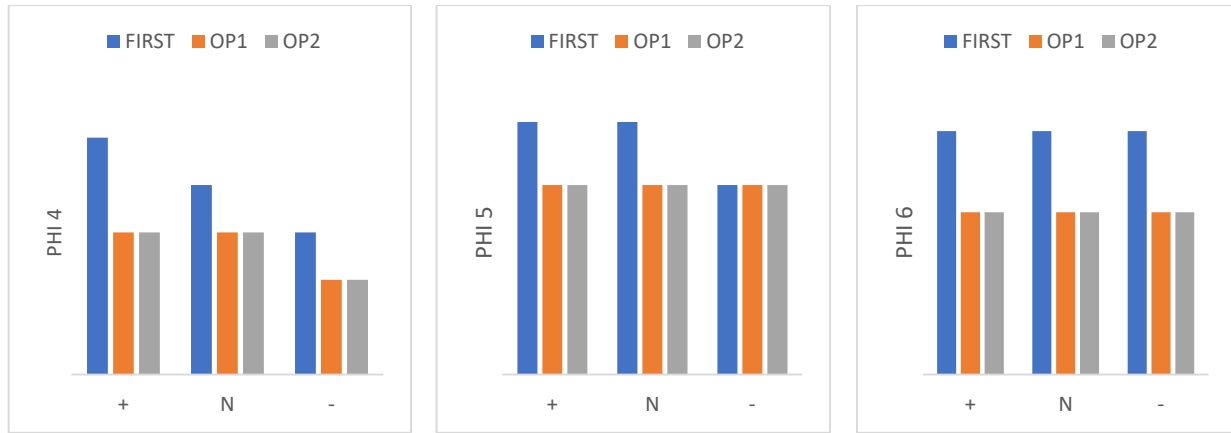


Fig. 16. Number of assets (facilities) (Owner)

Finally, in Fig. 17, the distribution of the best objective results found when applying the FePIA methodology is presented. It can be seen that most of the points are grouped to better assimilate the shocks and are closer to the area of budgeted values, improving the data obtained in the base scenario. Thus, the successful application of the FePIA strategy to measure the robustness and the scenarios considered to improve the supply chain design performance is confirmed.

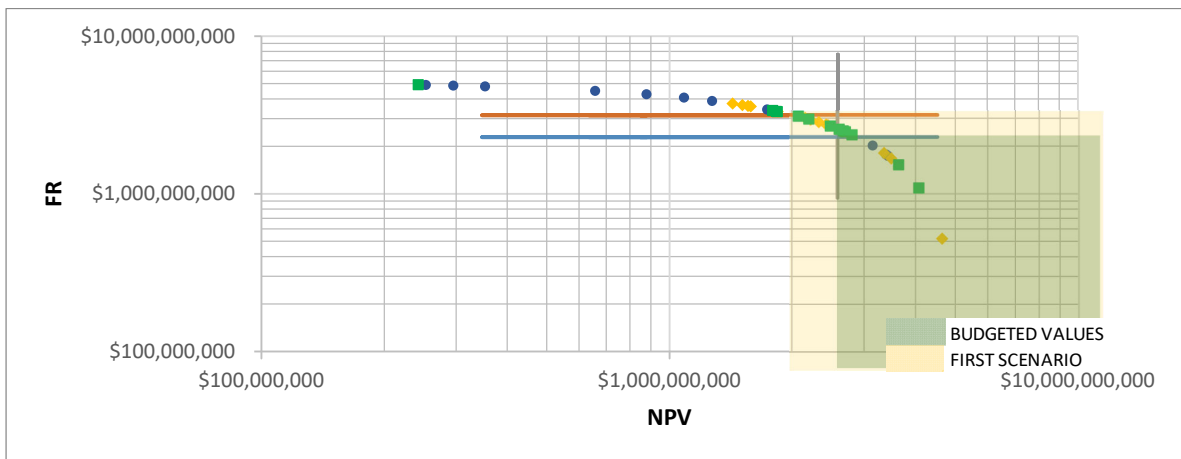


Fig. 17. Pareto solutions front with the best solutions found by FePIA methodology (Owner)

5. Concluding Remarks and Future Directions

This paper proposes a methodology for the robust optimization of multiobjective closed-loop supply chains by considering financial criteria and scenarios. The proposed method integrates closed-loop supply chains, such as the multiobjective optimization based on epsilon constraints and robustness measurements, through the FePIA methodology. Objective functions that maximize the net present value (NPV) and minimize the financial risk (FR) and parameter variability using scenarios were considered.

The proposed mixed-integer linear programming mathematical model was tested in the real case of a Colombian company in which each closed-loop supply chain link is represented, resulting in optimal events in terms of the proposed objectives. It was found that the company has lower profits than its budget and greater financial risk. Additionally, these results may be affected by a series of disruptions that affect the security of the investments, the company's requirements, and the operating characteristics, as could be seen with the FePIA strategy applied to measure the robustness of the supply chain.

Future research is recommended regarding the problems affecting a supply chain and defining each possible scenario's occurrence probability. It is also essential to know the likelihood that each scenario will occur. In this way, this parameter of the disturbance probability can be added to the mathematical model to enable strategic decisions with greater security. In the same way, we suggest using methodologies to solve stochastic models such as the sample average approximation (SAA), replacing the scenario-based method (Escobar, 2012; Escobar et al., 2013; Mafla & Escobar, 2015; Paz et al., 2015; Rodado et al., 2017).

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